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Using Business Intelligence for Operational Decision-Making in Call Centers

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ABSTRACT

This paper proposes an operational business intelligence system for call centers. Using data collected from a large U.S. insurance company, the authors demonstrate a decision tree based solution to help the company achieve excellence through improved service levels. The initial results from this study provide insight into the factors affecting this firm's call center service levels, and the solution developed in this paper provides two distinct advantages to managers. First, it enables them to identify key factors and the role they play in determining service levels. Second, a sliding window approach is proposed which allows managers to see the effects of resource reallocation on service levels on an on-going basis.

Keywords: *BI System, Business Intelligence (BI), Call Centers, Decision Trees, Service Levels*

INTRODUCTION

Calls centers are key organizational structures in a wide variety of industries, including the insurance industry (Callaghan & Thompson, 2001). Call centers were developed in part based on work done by Agner Erlang, the originator of traffic engineering and queuing theory (Angus, 2001). Erlang C is a mathematical formula that can be used to predict the most probable distribution of incoming calls based on historical data. By using the incoming call distribution, the appropriate number of phone lines and staff can be determined based on the trade-offs between costs and service quality (Townsend, 2007).

However, there is disagreement on the role and purpose of call centers, and there are two views of the cost vs. service trade-off. One view is that call centers are used by organizations as a way to reduce costs with customer service delivery a secondary consideration. The other view is that call centers can increase profits by maximizing customer service (Robinson & Morley, 2006; Li, Tan, & Xie, 2003). From either perspective a key concern of companies is "stickiness" or lock-in. Customers are more likely to leave or switch to another company

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if they have a bad experience or receive low service quality, and this can be true more-so in comparison with several other types of business interactions (Keiningham, Aksoy, Andreassen, Cooil, & Wahren, 2006). From either perspective, the effectiveness and service level provided by a call center is vital to the competitiveness of an organization (Lam & Lau, 2004).

The metric used for service levels in this study is a commonly used metric by call centers (Koole, 2003), used in industries and call centers well beyond the insurance call center in this study. Prior work shows it is related to customers' satisfaction with their call center experiences (Cronin, Brady, & Hult, 2000); in this study we examine the degree to which other variables impact service levels to help decision-makers more fully understand the metric they use, and to help them reallocate resources to maximize their service levels.

Determining which factors most significantly service levels is not straight forward, and approaches such as considering the number of calls answered does not necessarily equate to service. Traditionally call center service levels are based on capacity optimization for a given volume of calls. Our analysis shows that call volume is not related to service levels, implying that capacity is sufficient enough not have an impact on service levels. However, since neither capacity nor call volume explains service levels, managers are left wondering which variables do have effects.

Companies collect large amounts of data from their daily operations to help manage call centers. Computer-based decision support models have the advantage of sharpening information-processing skills (Curry & Moutinho, 1994), and the importance of implementing business intelligence tools to analyze and use this data is increasingly realized by many organizations. This paper demonstrates how business intelligence (BI) can be used to identify and analyze different factors affecting call center service levels in the insurance industry, which can lead to improved customer service while at the same time possibly maintaining or reducing costs.

BACKGROUND

Business Intelligence

Before the Information Age, businesses had no method to automate the collection, analysis, and interpretation of business data. Reports to summarize corporate metrics could take several months to generate. These reports allowed for informed long-term strategic decision-making, but little support was available for short-term tactical decision-making, prompting managers to rely on intuition for important daily decisions.

Business intelligence allows organizations to improve business performance by including the following technologies: Extract, Transform and Load (ETL); data warehousing and data marts; query, reporting and analysis; and XML web services (Bitpipe, 2008). Business intelligence supports three distinct types of users. The first are executives; executives need BI for strategic information showing the health of an organization, and for this purpose use BI tools such balanced scorecards, dashboards, and Key Performance Indicators (KPI). The second group of users are analytical users. Those users commonly employ on-line analytics processing (OLAP) tools with ad- hoc reporting capabilities for managing and planning. The third group are operational users, who use BI for frequently occurring short-term decisions. Operational users need BI output that is easy to use, such as flexible reports in formats like HTML, Excel or PDF (Information Builders, 2007).

Companies have much more data than they can analyze in a reasonable time frame. While precise numbers are difficult to determine, one industry study found that many businesses access only 20% of their data and deliver it to only 10% of the people that need it to do their jobs (Kenney, 2007). Part of the challenge is knowing what data is important to capture (Green, 2007). US corporations such as Google and Capital One Financial have begun to manage their employees and companies using data analysis (Thurm, 2007). But some report that 70% of enterprise content is recreated rather than reused (Kenney, 2007). This results in

Table 1. Business intelligence overview (adapted from Imhoff, 2007)

	Strategic BI	Tactical BI	Operational BI
Business focus	Develop long-term business goals	Manage tactical initiatives to achieve strategic goals	Manage and optimize daily business operations
Primary users	Executives & business analysts	Executives, analysts & line managers	Analysts, line managers, and operational processes
Time-frame	Months to years	Days to weeks to months	Intra-day
Data	Historical data	Historical data	Real-time, low-latency & historical data

redundant efforts to analyze data, and leaves executives looking for better solutions to get timely and effective competitive and market intelligence. Business intelligence is shedding its reputation as a report-generation tool only usable by certain executives and is giving integrated within the entire enterprise, from line-of-business managers to call-center or support-desk workers (Cincel, 2005).

Operational business intelligence focuses on applications within a daily timeframe (White, 2004). Frequently the data is intra-day with a low latency. Operational business intelligence supports line and process managers. Table 1 outlines the different foci of business intelligence; the insurance company's call center we analyze fits into the operational category.

Call Center Management

There are three basic value-added strategies call centers adopt. The first is to provide high-value added services with the associated higher costs of those services. The second is to minimize operation costs while providing acceptable levels of service. In the third, strategies focus on the trade-off between customer service and costs. Call centers can be classified by these strategies into three different levels: high value-added services, medium value-added services, and low value-added services; examples of each are described in Table 2 (Jobs, Burris, & Butler, 2007). The company studied here falls in the high value category.

For all of these strategies, a great deal of work has been completed in the areas of simulation and modelling of call centers. Often this work has looked at scheduling the trade-off between service and staffing levels to minimize the sum of cost and lost profits, or a the optimal configuration of hardware and software resources for telemarketing centers (Blake, Graves, & Santos, 1990). Our paper is modelling call center performance, but here we are focused the service level metric. This is a marked

Table 2. Value-added call center strategies

Strategy	Examples	**Result**
High value-added services	Financial services/banking/insurance; Government IT services/data bank	Highly customized products, high profit margins, more complex interactions with customers required
Medium value-added services	Telecommunications; Customer service; Directory services/job placement utilities	Higher mix of less routine inquiries and requests, such as billing issues and resolution of problems requiring some research and call back
Low value-added services	Fulfillment/distribution/reservations; Telemarketing/collections	Routine inquiries, lower profit margins

difference between our research and previous studies because many past efforts concentrate on answering operational questions such as (Mehrotra & Fama, 2003):

- How many agents should we have on staff with which particular skills?
- How should we schedule these agents' shifts, breaks, lunches, training, meetings and other activities?
- How many calls of which type do we expect at which times?
- How should we route our calls to make the best use of these resources?
- Given a forecast, a routing design, and an agent schedule, how well will our system perform?
- What is our overall capacity?

Call Center Performance Optimization

Our study focuses on service level, which is a macro-level performance issue. Some previous studies have looked at performance issues but their viewpoint is strictly from the manufacturing quality and efficiency point of view. For example, Omari and Al-Zubaidy (2005) discussed the performance metrics quality of service and efficiency of call centers. They defined quality of service as the probability of blocking a customer call due to the unavailability of a trunk, and efficiency based on agents' utilization and salary costs. This viewpoint of performance is markedly different from the one presented in this paper. Our study does have implications for scheduling, overall capacity, responding to calls, training, etc., as previous studies do, but is different because we are focusing on the underlying factors of service level. Most important, we are not considering the problem to be one of attempting to maintain a specific service level while holding some factor constant.

Historically operations researchers have used tools such as queuing theory (Hampshire & Massey, 2005), stochastic processes (Garnett, Mandelbaum, & Reiman, 2002), and simulations (Avramidis, Deslauriers, & L'Ecuyer, 2004) to model call centers. In addition, studies such as Atlason, Epelman, and Henderson (2004) include an identical definition of service level as we use. However, they are not attempting to model service levels, but are trying to maintain a specific service level while modelling staffing costs (i.e., they treat service level as a constraint). This paper also differs because we are not using a traditional modelling technique, but are using binary decision trees. Our decision trees allow us to easily see the impact on service levels of independent factors such as call volume, providing insight into aspects which may change over the course of a day.

The most common method organizations use to optimize call center performance is capacity planning (Blake et al., 1990). By making sure that the number of agents answering the phone meets the number of call coming in, a high service level can be achieved. But what is the next step? What do companies do after they have demand properly managed? The insurance company in this paper had the basic capacity management problems controlled. They have figured out optimal staffing levels, hours of operations, agents break schedules and lunches, and shift timing. In addition, agents' vacation requests and required training were considered a part of maximizing service levels. Most call centers are high-pressure work environments (Houlihan, 2000) where turnover is a major management problem. The high value-added call center studied here benefits from our solution because the decision tree allows managers to evaluate the underlying factors of service level and respond rapidly to changes in their environment.

DATA DEVELOPMENT

We analyzed data from a call center provided by a national insurance company. As part of the agreement to report this research, the identity of the firm is withheld. However, the call center is a U.S. operation that handles primarily North American calls. The data for this study was collected from an 18-month period and consisted

Table 3. Descriptive statistics from call center data

	Mean	Median	Std.Dev.
SERVICELV	0.922	0.9330	0.079
ACDCALLS	2008.485	1995.000	1269.089
ABANDONS	9.092	6.000	14.567
AHT	298.447	301.000	25.229
ASA	7.488	6.000	11.471
MAXDELAY	178.977	133.000	168.777

of 2,738 data points each with the following items aggregated into one hour intervals:

- DATE: Date of the calls
- WEEKDAY: Day of the week
- TIME: Hour of day ranging from 9:00 AM to 7:00 PM (one hour increments)
- ACDCALLS: The Automatic Call Distribution system (ACD) is a specialized telephone answering method that handles large volumes of incoming calls by distributing them equally among a group of agents on standard telephone lines (Lam & Lau, 2004). The ACD call is a metric that counts the number of calls that are routed through this system. All calls are routed through the ACD system unless a caller hangs up almost immediately.
- ABANDONS: Abandons are calls that enter the ACD system but the caller hangs up before being answered.
- AHT: Average handle time is measured in seconds including the call time and wrap up time after the call concludes.
- ASA: Average speed of answer is how many seconds a call center representative took to answer a routed phone call.
- MAX DELAY: Maximum delay is the time in seconds the longest call waited until either answered or hung up.

The description statistics from this data show some of the relationships between these variables and service levels and provide a context for analysis.

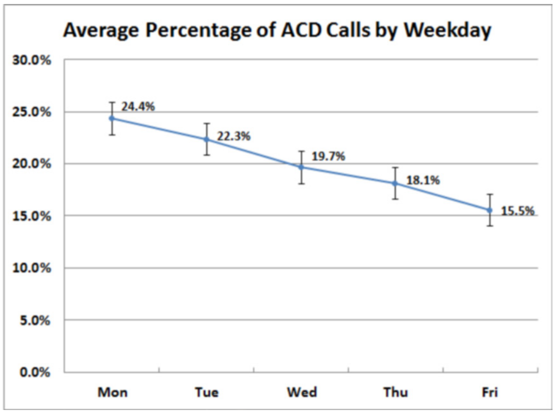
As can be seen in Table 3, this call center has an average service level of 92.2%, with a standard deviation of 8%. Data and time are not relevant for the descriptive statistics in Table 3 but can describe the patterns in call volumes as presented in Figures 1 and 2. Figure 1 shows the distribution of calls by weekday and shows that during the week call volumes steadily decreases from Monday to Friday; this pattern is consistent from week to week which is indicated by the bars for each day showing the range of plus or minus two standard deviations above or below the average volumes.

Figure 2 shows the average number of calls over the each hour of the day as a percentage of the total calls for the day. It shows that call volume builds through the morning hours to a peak which is followed by a decrease during the lunch hours, leading to a second peak during the afternoon.

A correlation analysis on all variables in the analysis is presented in Table 4. The results shows that date and time do not correlate with service level, although call volume correlates with both variables (at significance levels of .05 or less). Intuitively it makes sense that service level quality would suffer during high call volume times and excel during low call volume times. However, our analysis shows that is not the case. Although we have not done further analysis, we speculate that good staffing practices may be the reason. This is an important result to note because it tells us that we need to understand which can explain service levels.

Because they are not correlated with service levels and potential confounds, the variables

Figure 1. Percentage of total calls by weekday



for time and date were removed from the analysis. The data set for analysis therefore included service level (SERVICELV), weekday (WEEKDAY), number of calls (ACDCALLS), number of hang-ups, or abandons, (ABANDONS), average time to handle a call (AHT), average speed of answer (ASA), and maximum delay (MAXDELAY).

ANALYSIS AND RESULTS

The first step in developing our proposed business intelligence system is to create a decision tree predicting service levels. For our analysis, SERVICELV is the response variable to be predicted, WEEKDAY is a categorical variable, and the continuous predictor variables are ACD CALLS, ABANDONS, AHT, ASA, and MAXDELAY. There were 2,738 observations spanning the 18 month time period covered by this data set.

Statistica's implementation of CART (classification and regression trees) was used to create our decision tree. CART is preferable to earlier decision tree algorithms because it provides greater explanatory power and the ability to explain why a tree split is created (Breiman, Freidman, Olshen, & Stone, 1983). The resulting decision tree in Figure 3 provides insight into which variables have the greatest

Figure 2. Percentage of calls by hour of day

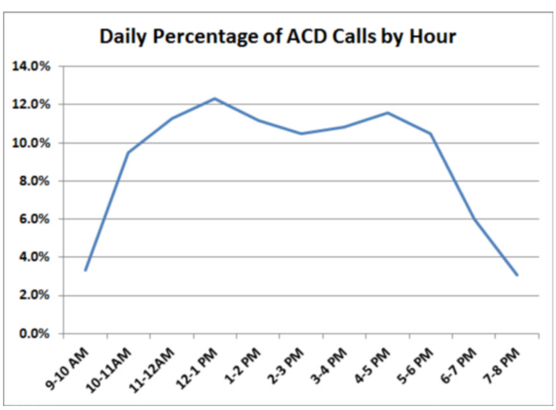


Table 4. Correlation matrix of service level factors

	ACD CALLS	WEEK DAY	TIME	SERVICE LV	ABANDONS	AHT	ASA	MAX DELAY
ACDCALLS	1.00	-0.32	-0.11	-0.09	0.07	0.02	0.06	-0.04
WEEKDAY	-0.32	1.00	-0.01	0.16	-0.17	0.08	-0.13	-0.02
TIME	-0.11	-0.01	1.00	0.00	0.35	0.31	0.02	0.39
SERVICELV	-0.09	0.16	0.00	1.00	-0.67	-0.07	-0.87	-0.42
ABANDONS	0.07	-0.17	0.35	-0.67	1.00	0.14	0.76	0.51
AHT	0.02	0.08	0.31	-0.07	0.14	1.00	0.06	0.14
ASA	0.06	-0.13	0.02	-0.87	0.76	0.06	1.00	0.43
MAXDELAY	-0.04	-0.02	0.39	-0.42	0.51	0.14	0.43	1.00

impacts on service levels, which is of key importance to managers for efficiently allocate scarce resources.

To interpret the decision tree shown in Figure 3, the leaf notes at the bottom of the tree show the predicted service levels based on splits in the variables leading down from the root node to that leaf. For example, the leaf node at the far right of the tree shows when average speed of answer exceeds 14.50 seconds then the predicted service level will be 74%.

Figure 3 reveals that average speed of answer (ASA) is used in the predictions leading to over half the leaf nodes. Average speed of answer is also the only variable influencing the first three levels of the decision tree, and most of the fourth level. This demonstrates average speed of answer is very influential in determining service levels. The next most influential variables are abandons (ABANDONS) and maximum delay; (MAX DELAY); they appear in four decision nodes (two each). Managers should improve call center performance in these areas to provide the greatest gains in service level. While weekday and average handle time (AHT) do appear in nodes of the decision tree, they are in only two non-leaf decision nodes far down the tree and so far less influential.

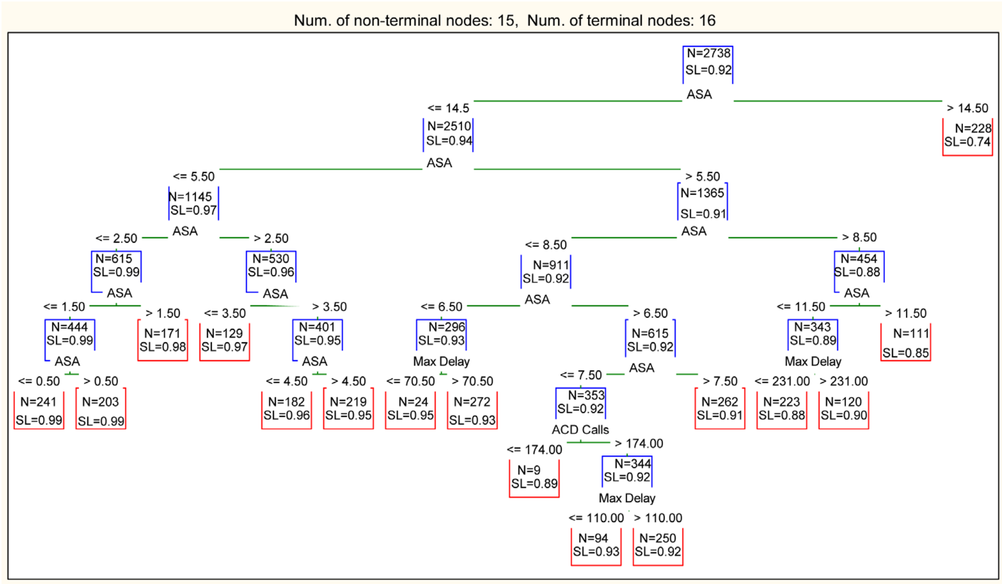
This decision tree model explains 74% of total variation in service levels. Statistica provides the mean square error (MSE) as a measure of accuracy with predictive decision trees. Traditional prediction methods, for example ordinary least squares regression, report R^2, which is the proportion of total variation explained by the model and known as the coefficient of variation, as a measure of accuracy. While not always used for decision trees, there are no statistical issues to using it, and R^2 does have the advantage of being a well-known measure directly comparable to measures produced by other algorithms. More importantly here, it is a single metric that is easier than some alternate measures for managers to interpret for a clear picture of how much of the variation in service levels the decision tree explains. R^2 is calculated as:

$$R^2 = \sum\left(\hat{Y} - \overline{Y}\right)^2 / \sum\left(Y - \overline{Y}\right)^2$$

where $\hat{Y}$ is the predicted value, Y is the observed value, and $\overline{Y}$ is the mean of the observed values.

The decision tree is useful for predictions of future service levels based on this set of variables. If current values for variables like average handle time and average speed of answer stay approximately the same, it is reasonable to predict that service levels will not vary greatly in the near future. While there are sources of variation in service levels that this decision

Figure 3. Decision tree for predicting service levels



tree does not account for, and while it is less than twenty-six per cent of the total variation.

Based on these results and supported by a decision tree that explain a high percentage of the variation in service levels, call center managers should first spend resources on reducing average speed of answer times to less than 14 seconds. This assures that mean service levels will be in the 90th percentile. Approximately 91% of calls have average speeds of answer less than 14 seconds, leaving close to 8% of calls with mean service levels of 74%. Within the 91% of calls with less than 14 second answer times, 54% have answer times between 5.5 and 14.5 seconds, corresponding to mean service levels of 91%. While this sounds good the call center strives for service levels at or above 96%, affording plenty of room for improvement. To achieve the 96% mark average speed of answer times will have to be less than or equal to 5.5 seconds.

Constructing a decision tree and determining key factors is an important first step, but alone is not sufficient to provide continuing operational support to managers. What we propose is a system that uses a sliding window for continually reconstructing decision trees and highlighting the factors impacting service levels. This is critical because as mangers reallocate resources the impacts individual variables have on service levels change. In a sliding window approach, data from calls during a prior "window" of fixed length are used to reconstruct a decision tree, which is then compared with trees constructed using call data in earlier windows to detect changes. We envision a system that shows how increased efforts to reduce average speed of answer impact service levels with data summarized at the hourly level. Finer grained analyses from smaller window sizes might be feasible, but preliminary analysis shows that reconstructing the decision trees from the windows immediately prior to once or twice a day is likely sufficient to detect the effects of changes in conditions and resource allocations.

Moving window techniques are useful in estimating time-varying model parameters and to construct adaptive responses assuming stationarity (stability of mean and variance) to hold only locally in time (Dahlhaus, 1997). Determination of the length of the time window requires compromise, since a long time window results in a small variance at the expense of a possibly large bias, i.e., the series may include non-stationary features. On the other hand, separating quasi-deterministic effects (such as cycles) from stochastic variations is difficult with a short series.

Clearly the important question is how to detect a change in the structure of the data as a result of underlying changes occurring in the call center. In a case involving time series data such as this, the auto- and cross-correlation structure of those series can serve as a basis for judging an appropriate window length by noting the points at which predictive accuracy is lost (e.g., significance of correlations at a given lag). But this approach depends to a certain extent on the degree of stationarity of the variance for both individual series (auto-correlation structure) and for the set of series (cross-correlation structure). If the change in volatility of an individual series is gradual and recurring, and its cross-correlations with other series are likewise stationary, a time window of a fixed size may suffice. If the change in volatility of the series is abrupt (e.g., shifts) and non-recurring, or if both types of change occur, the size of the time window would have to adapt to the speed of change.

Although the patterns in overall call volumes are fairly consistent, in most call centers including this one there are continuous changes in the nature of calls which are reflected in the data items used in our analysis. To ascertain the effects of those changes on service levels, having recent data is essential. However, the question is how much data should be used – how far back in time to go with the data for the analysis. In part it depends on the duration of the impact of those changes on service levels. If we operationalize a sliding window that includes too much data from previous years, then we are sampling from heterogeneous populations that are likely biased by data that does not represent changes due to the recent reallocation of call center resources. It also depends on the transience of those changes. There is always some amount of natural instability in service levels due to changes over time in call center representatives, customers, and changing policies. A balance between duration of effects and transience is essential; our experience with this company was that an appropriate window size was twice the length of the reporting timeframe, which in this case was one day. This suggests that a window of two days long is a productive starting point.

DISCUSSION

This proposed business intelligence system aids management decision-making in two ways: First, decision-makers can study the decision tree and isolate the variables affecting the response variable service level. Figure 3 shows that of the six variables entered into the analyses, the first of the five included in the decision tree, average speed of answer (ASA) is the most important, followed by the abandons (ABANDONS) and maximum delay (MAX DELAY), and lastly average time to handle a call (AHA), and weekday. This provides managers with information regarding the relative importance of variables on service levels, and if used with a sliding window allows decisions in resource allocations to be evaluated by call center managers.

Call volume was not found to be useful in predicting service levels here. The finding that service levels do not necessarily fall during peak periods, even when those period are extended in duration, might seem counterintuitive and is important because it suggests managers should focus on improving the treatment of existing calls instead of focusing on reducing call times or volume, or by shifting calls to smooth out the peaks.

The final step in the economic rational choice process (Cyert, Simon, & Trow, 1956) involves searching for problems on which an organization should focus their attention. By knowing which factors are most important determinants of service levels, managers are able to turn their attention to what underlies those factors. This suggests that further study of each factor is necessary to determine the extent of the organization's influence over the factor. Average speed of answer (ASA) is a dominant factor as shown in the decision tree in Figure 3. However, the decision tree doesn't have the ability to perform a sub-analysis of the variable average speed of answer. If the organization wants to improve service levels they should learn what antecedents determine average speed of answer. This may involve collecting new data, or studying how efficiently the automatic call distribution system performs.

CONCLUSION

Operational business intelligence provides opportunity for organizations to gain a competitive advantage by providing insight into daily processes that may not be fully understood by their managers, with advantages accrued that are well documented in both academic and professional literature. In particular, call centers can provide clear competitive advantages for insurance companies. This is a clear call for research into ways to create and implement business intelligence systems utilizing data currently collected by organizations.

Our solution for achieving improving call center service levels provides call center managers knowledge of the factors most influencing their service levels. For this company, the results show that average speed of answer is the factor accounting for the greatest variation in service levels. The next step for management is to work towards ensuring answer times are low as possible. To achieve this, more analysis can be conducted to evaluate factors hypothesized to influence answer times. While changes are being made modelling new data with decision trees provides a means for managers to continually monitor how each factor affects service levels. Currently the organization would like all service levels to be at or above 96%. Our analysis shows this is possible for average speed of answer times under 5.5 seconds. Knowing which factors are most critical for service levels helps the company know what to emphasize in their training programs for representatives, and gives them a more solid basis and criteria for performance reviews to formulate change to their commission structure. Our choice of a decision tree was a purposeful attempt to create a more intuitive BI system. The issue of model type and output has been addressed in previous research (Hoch & Schkade, 1996; Kottemann & Remus, 1989). We believe our output allows decision-makers to understand the underlying model without the need for strong quantitative skills and will thus be more likely to use the model to improve decision-making.

There exist several possible directions for future research. First, software can automate rebuilding the decision tree construction based on a weekly (or daily, monthly, etc., depending on the company) sliding window of accumulated data. This could lead to further insights about changes that affect speed of answer and delay times impact service levels. This is critical for managers to gauge the success of resource reallocation. Second, while the decision tree showed that 74% of the variation could be explained, there is still some unexplained variation and likely there are additional outside factors affecting service levels. More research needs to be done to help isolate these factors.

In addition, research can be conducted to see if decision trees are the optimal choice for this form of predictive model. We chose decision trees because they are easy to interpret for managers who might not be well-trained in data analysis. This is important because the system will identify factors that have the greatest impacts on service levels, possibly leading to a reallocation of resources. Finally, a complete operational system based on the solution demonstrated in this paper could be augmented with the capability of providing timely guidance regarding changes in the structure of operational parameters over time. A moving (sliding) time window of fixed length as proposed here is a reasonable first step in creating that capability, but does not address the most appropriate characteristics to use for determining the size of that moving window; future research could focus on finding those characteristics.

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